Advances in Precision Farming: a contribute for estimating crop health and water stress by comparing UAV Multispectral and Thermal Imagery

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Abstract

Current climate change is largely due to the continuing increase in the anthropogenic greenhouse effect, with major environmental repercussions, especially in agriculture. The increase of global warming, salinity of water resources and frequency of extreme weather events has devastating consequences on the primary sector, in particular on the photosynthetic activity of crops and, therefore, their agricultural yield. The current climate crisis, in fact, leads to an increase in water requirements, the proliferation of weeds, and the depletion of nutrients in the soil, necessitating the massive use of fertilisers, herbicides and pesticides, which, in turn, trigger substantial alterations in ecosystem balances. In response to these critical issues, precision agriculture (PA) constitutes a data-driven approach based on the interpretation of multispectral and thermal datasets obtained by different remote sensing techniques and the use of latest-generation sensors to recognise the state of health of crops and, therefore, optimise agricultural production with a more rational and sustainable management of resources.

This paper presents the results of a survey campaign carried out in October 2023 on two citrus fields located in south-eastern Sicily (Italy) to highlight the health status of crops just before the harvesting period. By using multispectral and thermal sensors installed on a drone, different vegetation indices have been calculated to identify, in each field, the areas with the highest photosynthetic activity and the zones characterised by a lack of water or other nutrients, on which targeted agronomic interventions should be planned as a priority

1. Climate change and agriculture

The steady rise in temperatures over the past 150 years is causing growing concern about the problems it causes globally, from imbalances in environmental ecosystems to human and social repercussions. While life itself on the planet is guaranteed by the presence of greenhouse gases in the atmosphere (CO2, methane, but also water vapour) that retain part of the sun's rays reflected from the earth's surface, ensuring an average temperature of around +15 °C, the addition of the anthropogenic greenhouse effect causes an excessive rise in the amount of heat present on earth. According to the Intergovernmental Panel on Climate Change (IPCC), in fact, the earth's average temperature has increased by 0.98° Celsius compared to pre-industrial levels, and forecasts show that, if no action is taken, this value could increase by a further +1.5° in the next twenty years. The impacts of this warming are widely known, such as: the reduction of Arctic sea ice with consequent rise in sea levels (salinity of water resources), an increase in the frequency of extreme weather events such as cyclones, floods, acid rain, but also heat waves and periods of drought, which have direct consequences on both agricultural productivity and the very health of the population.

With regard to the primary sector, which is essential for the very existence of humanity, the effects of the current climate crisis are multiple and affect both crop productivity and the sustainability of agricultural practices. Increased temperatures, as is well known, tend to cause water stress in species that are less resistant to heat waves, reducing the photosynthetic activity of the plant and, therefore, its agricultural yield. On the other hand, the difficulty of forecasting models to anticipate extraordinary weather events, such as long periods of drought followed by intense rainfall, does not help neither to efficiently manage water resources nor to prevent flooding, siphoning phenomena in fields and related problems of root system failure. All this also facilitates the proliferation of pests and diseases that compromise the health of crops and require pesticides and herbicides to eradicate them.

In the light of these reflections, considering also the population increase beyond 9.7 billion by 2050, as estimated by analyses conducted by the United Nations, it is clear that agriculture plays a crucial role in combating the climate crisis, especially in terms of production yield, to continue to meet the food needs of all humanity in the near future. In particular, considering the already limited availability of water resources in agriculture, for the foreseeable future it becomes absolutely necessary to make the use of water more efficient with sophisticated irrigation scheduling strategies that take into account the actual water stress conditions of crops.

In response to the ongoing climate crisis, for several decades now, many studies have been concerned with the intrinsic relationships between climatic-environmental parameters and productive green (Chen et al., 2021; Khikmah et al., 2024) developing a significant paradigm shift in the management of the agricultural sector: the so-called Precision Agriculture (PA), or Precision Farming (Zhang et al., 2023). It is a data-driven approach strongly oriented towards the optimisation of agricultural production and an increasingly rational and sustainable management of resources through the multidisciplinary integration of information datasets from various sectors (geomatics, agronomy, engineering, computer science, etc..) brought together through the use of different remote sensing techniques (from satellite or Unmanned Aerial Platform-UAV), the use of the latest generation of sensors (such as multi/hyper-spectral optics and high-resolution thermal cameras), geographic information systems (GIS) and global positioning systems (GPS), and the application of artificial intelligence algorithms (Say et al, 2018; Tantalaki et al., 2019; Weiss et al, 2020; Niyonzima,2024).

Although lagging behind the international context, in the last five years even the Italian primary sector has become increasingly interested in the principles of PA, recognized and regulated by Ministerial Decree 33671 of 22/12/17: it is in this perspective that the here presented work fits in, which concerns the results obtained from a survey campaign carried out in October 2023 on two citrus fields located in south-eastern Sicily

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(Italy) using multispectral and thermal sensors installed on a drone.These surveys are part of a broader multi-year monitoring activity of several orchards belonging to the historical farm 'F.lli Solarino', which, for some years now, has been optimising its business management processes by implementing the PA to increase the quality of its production of organic oranges, lemons and grapefruits and to face the increasingly stringent market challenges.

2. Precision agriculture and vegetation indices

Remote sensing techniques applied to the primary sector are based on the measurement of the spectral reflectance of crops, also called albedo and understood as the ratio of the amount of energy reflected by the leaf surface to the incident energy. The interaction with the chemical composition and physical structure of the invested surfaces, in fact, alters the percentage of reflected solar radiation in the different ranges of the electromagnetic spectrum (Sishodia et al., 2020; Sansare et al., 2020), transforming it into an identification signature, called a spectral signature, capable of distinguishing one reflecting body from another. The acquisition of the spectral signatures of crops, supplemented by an in-depth knowledge of the vegetation species, the age of the plant, the chemical composition of the soil and the climatic parameters (rainfall rate, temperature trends), represents, therefore, the essential data for recognising their state of health, i.e. the presence of good photosynthetic activity (high concentration of chlorophyll), correct water content at leaf level and nutrient content at global level (Gavrilovskaya et al., 2021).
After acquisition, in fact, the multispectral datasets are analysed and interpreted through the calculation of the so-called vegetation indices, i.e. some mathematical formulas applied to the pixel values of the remote sensing multispectral images, which are useful to assess crop vigour, biomass density and, more generally, ecosystem dynamics (D'Urso et al., 2018; D'Urso et al., 2024). These numerical indicators combine the values of reflected radiation in different ways according to certain wavelengths in specific bands of the electromagnetic spectrum: for photosynthesis activity, for example, the chlorophyll present in a healthy leaf absorbs more red radiation while the chloroplasts in the cell walls of the parenchyma retain ultraviolet and blue radiation; on the other hand, the green and near-infrared (NIR) bands are almost entirely reflected. It is clear, therefore, that reflected energy values in the red and near-infrared ranges, measured using high-resolution multispectral cameras and thermal sensors mounted on Unmanned Aerial Vehicles (UAVs), underlie the calculation of most vegetation indices (Sansare et al., 2020; Buitink et al., 2020; Del Castillo et al., 2018).
Among these, the most widely used indicator in PA remote sensing applications is undoubtedly the normalised differential vegetation index (NDVI), which, as Table 1 shows, measures reflectance values in the red and near-infrared regions to obtain useful information about the growth level of the crop and its vigour. NDVI values close to 1 indicate healthy green growth, while negative values (-1 min value) identify the absence of photosynthetic activity, and thus identify non-vegetation surfaces such as urban areas, water or ice. Despite being widely used and easily interpreted, the NDVI is significantly affected by some external environmental factors, such as the effects of soil brightness, atmosphere, clouds and shadows cast by canopies. In addition, this indicator tends not to be fully reliable in presence of high-density vegetation, as it misinterprets high biomass concentration as very healthy vegetation. To overcome these criticalities, the NDVI analysis can be supplemented with the calculation of other vegetation indices, always normalised with values between -1 and 1, some of which are shown in Table 1. The Modified soil adjusted vegetation index 2 (MSAVI2), for example, minimises the backscattering radiation reflected from the ground: for this reason, it is particularly suitable for studying arid or semi-arid contexts in which vegetation is sparse or limited (D'Urso et al., 2023). On the other hand, the Green Normalised Difference Vegetation Index (GNDVI), by replacing the red band with the green band, significantly increases the sensitivity to the presence of chlorophyll and reduces interference due to the soil, thus becoming particularly effective for analyses of contexts with low and diffuse vegetation (Mediterranean scrubland).

Index	Definition/Equation
Normalized difference vegetation index – NDVI	$\frac{(\rho_{NIR} - \rho_{RED})}{(\rho_{NIR} + \rho_{RED})}$
Green normalized difference vegetation index – GNDVI	$\frac{(\rho_{NIR} - \rho_{GREEN})}{(\rho_{NIR} + \rho_{GREEN})}$
Modified soil adjusted vegetation index 2 – MSAVI2	$0.5 * \left[(2\,\rho_{NIR} + 1) - \sqrt{(2\,\rho_{NIR} + 1)^2 - 8\,(\rho_{NIR} - \rho_{RED})}\right]$
Red edge normalized difference vegetation index – NDRE	$\frac{(\rho_{NIR} - \rho_{RED\,EDGE})}{(\rho_{NIR} + \rho_{RED\,EDGE})}$
Chlorophyll Absorption Ratio Index - CARI	$\frac{\rho_{700}}{\rho_{670}} \times \frac{a * \rho_{670} + b * \rho_{670}}{\sqrt{a^2 + 1}}$
Modified chlorophyll Absorption Ratio Index - MCARI	$\frac{\rho_{RED\,EDGE}}{\rho_{RED}} \times [(\rho_{RED\,EDGE} - \rho_{RED}) - 0.2(\rho_{RED\,EDGE} - \rho_{GREEN})]$
Chlorophyll index - CI	$\frac{\rho_{NIR}}{\rho_{RED\,EDGE}} - 1$
Chlorophyll vegetation index - CVI	$\frac{\rho_{NIR}}{\rho_{GREEN}} * \frac{\rho_{RED}}{\rho_{GREEN}}$
(Crop Water Stress Index)$_{statistic}$ – CWSI$_{statistic}$	$\frac{T_{coltura} - T_{wet}}{T_{dry} - T_{wet}}$

Table 1. Some of the most used vegetation indices for remote sensing applications in precision agriculture

Special consideration can be given to certain spectral indices developed to specifically monitor the presence of chlorophyll at leaf level as a direct indicator of the plant's primary biomass production and its photosynthetic potential. Reflectance in the Red-Edge region is often used for this purpose as it is able to penetrate deeper into the leaf structure than the red band that is absorbed by chlorophyll in the first layers. The Chlorophyll Index CI, for example, is a function of the simple ratio of the reflected radiation in the near-infrared band to that in the red-edge, while the Normalized Difference Red Edge Index (NDRE), calculated as shown in Table 1, is a good indicator of crop health in the advanced stages of growth, when the chlorophyll concentration is highest (thus exceeding the saturation limit of the NDVI in large presence of biomass). Other interesting indicators are the Chlorophyll Absorption Ratio Index (CARI) and the same index modified by Daughtry et al. (2000) (MCARI) to improve sensitivity to chlorophyll uptake. These indices make it possible to estimate the

chlorophyll absorption ratio to localise any anomalies: high CARI/MCARI values, in fact, are due to low chlorophyll concentrations, a symptom of the presence of pathogenic elements (bacteria/insects), the precise localisation of which allows rapid and targeted management of the problem with timely phytosanitary treatments. These indicators, however, are particularly sensitive to the reflectance properties of the soil, being more reliable in the presence of high-density crops (wheat fields, cereals, etc.). On the contrary, the calculation of the Chlorophyll vegetation index (CVI), a function of the ratio between reflectances in the red, green and NIR regions, is more suitable for agricultural areas with low leaf area indices.
In addition to these indicators, the use of thermal sensors to precisely detect crop temperature, a fundamental parameter that influences the physiological processes of vegetation, such as evapotranspiration and the concentration of photosynthetic activity, has proved particularly interesting. Temperature and water content are in fact two intrinsically linked aspects: while, on the one hand, the loss of water through transpiration is a necessary process to lower plant temperature, on the other hand, excessive transpiration due to rising temperatures can cause an imbalance in the water content at leaf level, which is essential for growth and cell division. In other words, the plant comes to lose more water than it can absorb from the soil, creating a condition of water stress that can lead to the withering of the crop itself, drastically reducing photosynthesis activity. Monitoring, therefore, the surface temperature of crop canopies by means of thermal sensors that detect radiation in the mid- and far-infrared band is an important indicator (Crop Water Stress Index - CWSI) for the detection of possible water shortages (Messina et al., 2020). Over time, several indicators have been developed to quantify this water stress: some based on the relationship between the vegetation/air temperature gradient and the vapour pressure deficit (Idso et al., 1981), others on the canopy energy balance (Jackson et al., 1981).
Conversely, the empirical approach for the calculation of the CWSI consists in calculating the normalised canopy temperature by taking the temperatures of the wet canopy (Twet), i.e. when the leaves are wet and therefore fully transpiring with open stomata, and of the dry canopy (Tdry), when the leaves are not transpiring at all. Since all these formulations are somewhat dependent on meteorological-environmental factors, which are not always readily available, it is often more suitable to calculate the statistical CWSI (Cohen et. al., 2017), which estimates the Twet as the mean value of the lower 5% fractile of the distribution histogram of the measured temperatures, and the Tdry as the air temperature increased by 5°C, as indicated by the formula shown in Table1. The higher the CWSI value, the closer the crop is to a condition of water stress, and thus to a reduction in chlorophyll synthesis to conserve water. To identify the health status of crops, it is therefore particularly useful to analyse these thermal indices in parallel with the spectral indicators developed to detect chlorophyll levels, such as NDRE, CI and CVI.

3. Geographical framework of the case study

An innovative integration between vegetation indices calculated from multispectral datasets and indicators directly linked to water stress detection was tested on two citrus grove fields located in south-eastern Sicily (Italy) to monitor their state of health and identify any areas affected by water or nutrient deficiencies before the beginning of the harvest season. The first test area, of approximately 5.6 hectares, is located in the Pontevecchio locality (36°51'15.0 ‘N 15°00'28.0 “E) along the south-eastern Sicilian state road that connects the towns of Rosolini and Noto; the second test field is located along Provincial Road 46 on the southern outskirts of the town of Ispica (36°46'05.8 ”N 14°54'14.5 ’E) and extends over approximately 3 hectares (Fig.1).

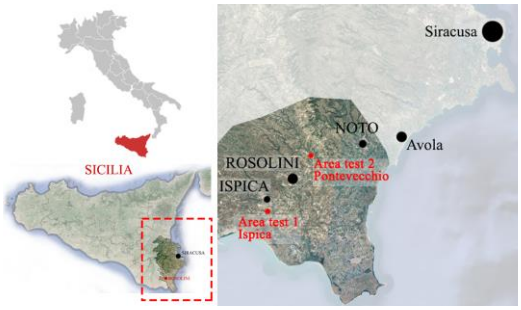

Fig. 1 – Geographical framework

Geographically the two orange groves are located in the so-called Valle di Noto, situated between the provinces of Siracusa and Ragusa, and characterised by a hilly landscape with gentle undulations and valleys alternating with more massive reliefs, such as the Iblei mountain chain, to the north, which form a sort of natural barrier. The relative proximity of the sea also favours mild climatic conditions with temperature gradients and humidity levels that make the area particularly suitable for growing citrus fruits and vineyards (in the winter, temperatures do not fall below 10°C, while in the summer, the highest peaks are around 40°C). Thanks to the application of the principles advocated by the PA through planned monitoring on a multi-year scale, the company that owns the two citrus groves (‘Bioagricola F.lli Solarino’) has been representing a virtuous model of optimization of business management processes for some years now. This model aims for quality production capable of responding to consumer needs by pursuing sustainable processes.
The results presented in this work constitute the founding operational procedures of this innovative approach that uses multispectral and thermal datasets to recognize the state of the vigor of citrus groves as an indispensable knowledge base for improving the efficiency of agricultural practices, i.e. favoring a rational use of resources (e.g. by reducing the water wastage of traditional sprinkler irrigation with more concentrated watering in areas under water stress) and employing so-called "useful insects" (e.g. ladybirds) instead of classic pesticides to contain and control the action of crop-damaging pests in an eco-sustainable manner.

4. Methodology and survey

The precision photogrammetric survey for the acquisition of the multispectral and thermal datasets useful for the elaboration of the proposed analysis methodology was carried out using state-of-the-art sensors installed on a UAV platform with high flight autonomy, so as to guarantee the complete acquisition of each field with a single flight plan.
Specifically, the pre-calibrated Micasense RedEdge-M Multispectral sensor was used, capable of simultaneously registering 5 multispectral bands (B1=blue; B2=green; B3=red; B4=red-edge; B5=NIR) with a spatial resolution of 1280 x 980 px, pixel size of 3.75 x 3.75 μm and focal length of 5.5mm. The FLIR XT2 thermal radiometric sensor with a Focal Plane Array (FPA) was used for reflectance measurements in the thermal infrared range, which returns a spatial resolution of 640 x 512 px, pixel size of 91.9 x 115 μm and focal length 13mm. Following the acquisition phase, the entire photogrammetric

datasets of each field were imported into the Agisoft Metashape software and grouped using the multi-camera system.

	PONTEVECCHIO		ISPICA	
	Multisp. Survey	Termic Survay	Multisp. Survey	Termic Survay
Nr. of images	3170	708	1895	717
Flying altitude	64.8 m	212 m	71.7 m	79.5 m
Ground resolution	4.39cm/pix	6.77mm/pix	4.91cm/pix	4.85mm/pix
Tie points	1.110.758	469.010	871.630	718.775
Projections	6.697.116	1.561.008	3.527.174	2.446.659
Reprojection error	0.759 pix	10 pix	3.55 pix	1.13 pix

Table 2. Technical specifications of each acquisition campaign

In this way, the totality of the multispectral images acquired were subdivided in relation to the number of channels recorded during the survey phase, resulting in a smaller number of images to be processed (which, however, retain all the multispectral information detected within them) and, therefore, a significant reduction in processing time. Having used a pre-calibrated multispectral sensor, it was not necessary to enter the calibration data of the camera into the programme; instead, with regard to the thermal sensor, it was decided to confirm the calibration parameters estimated by the software itself. With the subsequent alignment phase, the different positions of the cameras were identified, determining the orientation of each image and the points of correspondence between them. To verify the accuracy of these calculations, positioning maps of the cameras were obtained from the software, including a graphic display of the estimated localisation errors.
As can be seen, by way of example, in Fig.2 (flight plan of the Ispica field), in these maps the shooting positions recognised through the image alignment process are indicated as black points, while the ellipses centred on these points identify the estimated errors: the error along the z axis (in height) is represented by the colour of the ellipses, while their shape highlights the error in positioning the camera along the x and y directions. Specifically with respect to the Ispica field, for example, it can be seen from Fig.3 that the majority of the ellipses are green in colour and, therefore, there are no significant positioning errors in height; the almost circular shape of the ellipses and their small size also suggest that the positioning error in the xy plane is not very significant and homogeneous with respect to the two directions. Table 2, however, shows that the reprojection error is 3.55pix, which is relatively high considering a ground resolution of 4.91 cm/pix.
This inconsistency can be understood by observing, again on the positioning map of the cameras, the presence of a number of larger, blue ellipses which, although influencing the value of the general reprojection error, actually refer to the area of the provincial road, with respect to which the survey was influenced by the updrafts due to the increase in asphalt temperature, causing greater rolling and pitching effects, with relative instability. On the other hand, the same analysis conducted on the citrus grove at Pontevecchio returns estimated errors that are almost irrelevant in all three directions x,y,z, as is also confirmed by the very low value of the reprojection error indicated in Table 2 (0.759 pix with a ground resolution of 4.39 cm/pix).
After these necessary operations, the Dense Point Cloud, the Digital Elevation Model (DEM) and, lastly, the multispectral orthomosaic were generated, as the basis from which the already presented vegetation indices were calculated, fundamental for studying the vigour state of the citrus grove.

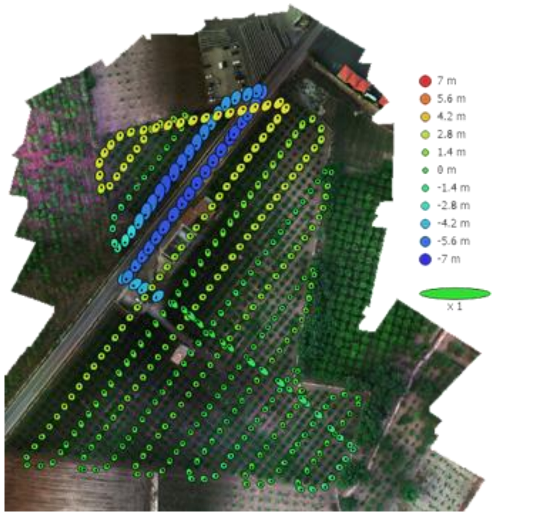

Fig. 2 – Ispica field: flight plan and estimated errors

From an operational point of view, the multi-band orthomosaics were exported in GeoTiff format, to retain the geographical and multispectral information, and loaded into the QuantumGis software, where the input of the different mathematical formulae into the Raster Calculator made it possible to obtain the graphic processing of the NDVI, MSAVI2, GNDVI, NDRE, CI and CVI indicators (Fig.6-7). Finally, by processing the raster statistics, the average values of each index were calculated for both test areas, as also shown in Fig.6-7.

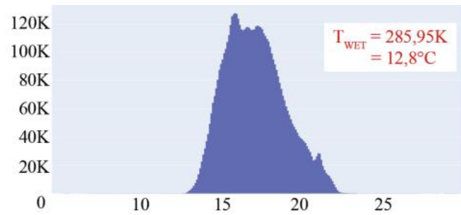

Fig. 3 – Ispica Field: Temperature distribution histogram

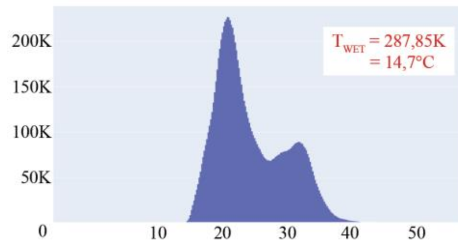

Fig. 4– Pontevecchio Field: Temperature distribution histogram

The same methodology was applied for the elaboration of the thermal orthomosaics from which the CWSI indices were derived by applying the previously described statistical approach. Specifically, the histograms of temperature distribution in the two test fields were extracted from the calculation software, as seen in Figs. 3 and 4, thanks to which it was possible to estimate the T_{wet}, necessary for the calculation of the CWSI, as the average of the lower 5% of the temperature values recorded during each survey campaign. For the field near Ispica, a T_{wet} value of 285.95K, or 12.8 °C, was obtained, while on the citrus grove in Pontevecchio the lower temperature was calculated to be 287.85K, or 14.7 °C. Consulting the climatic datasets, freely available for the entire region of Sicily, it was instead possible to identify the maximum temperatures recorded in the two localities on the exact day on which the survey was carried out (T_{max} Ispica=26°C; T_{max} Pontevecchio=27°C): these values increased by 5°C, as suggested by the statistical method for calculating the water stress index, returned the T_{dry} quantities to be used in the formula, equal to 31°C for Ispica and 32°C for Pontevecchio. Therefore, using the T_{wet} and T_{dry} parameters thus obtained, it was possible to calculate the water stress indicators by entering the formula in the software's raster calculator to derive the graphic displays of the CWSI as had been done for the other vegetation indices. To make the reading of these calculations clearer, a colour scale was chosen which, from blue to red tones, associates increasing values of CWSI, and thus of water stress.

5. Results

Analyzing the spatial distributions of the vegetation indices calculated for the two test fields (Figs. 6-7) and the direct comparison of the relative average values shown in the graph in Fig.5, two important considerations immediately emerge: on the one hand, significant differences can be identified concerning the state of vigor of the plants within the same orchard, which correspond to the precise location of more luxuriant areas with regard to areas that are considerably more critical; on the other hand, it can be seen that the values returned by the indicators referring to the citrus grove near Ispica are considerably lower than those concerning the field in Pontevecchio.

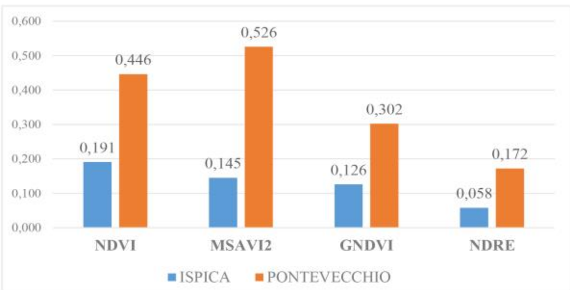

Fig. 5–Ispica and Pontevecchio fields: comparison between normalized mean vegetation values

This diversity affects all the vegetation indices, starting from a minimum decrease of -0.114 referred to the NDRE index, up to the greatest difference (in absolut valude) detected by the MSAVI2 indicator, with an average value of 0.145 recorded in Ispica, compared to the average of 0.526 observed by the same index on the Pontevecchio field.

Another interesting aspect is the difference between the values of the vegetation indices calculated using the NIR and Green bands: in fact, in both fields the average values of the GNDVI indicator are slightly lower than the corresponding NDVI values [$\Delta(\text{NDVI-GNDVI})_{\text{Ispica}}$=0.065; $\Delta(\text{NDVI-GNDVI})_{\text{Pontevecchio}}$ =0.144]. These are slight variations that are, however, significant in relation to the very reliability of these indicators: since the survey was conducted shortly before the harvest season, it is reasonable to assume that the plants were in their maximum period of leaf development and this, as previously explained, has a negative effect on the calculation of the NDVI which, by its definition, saturates rapidly in the presence of high leaf density, returning values that are not fully reliable with respect to reality. In this case, therefore, the average values obtained using the reflectance in the green band are more reliable. This observation is also confirmed by comparing the spatial distributions (Fig.6-7) of the GNDVI index with those of the index calculated using the Red-Edge band (NDRE). In both test areas, in fact, the areas of the citrus groves characterised by the concentration of high GNDVI values, visualised with tones tending towards green/yellow, correspond precisely to the areas where the NDRE values are higher, i.e. where photosynthetic activity is higher and therefore the citrus groves are more vigorous and healthy. This is even more evident when analysing the maps of the CI and CVI chlorophyll indices which, although they are not normalised indices, record the highest amounts of chlorophyll [$(\text{CI}=1.53 \text{ and } \text{CVI}= 6.19)_{\text{Ispica}}$ and $(\text{CI}= 2.74 \text{ and } \text{CVI}= 6.00)_{\text{Pontevecchio}}$] precisely in the same areas already highlighted by the GNDVI and NDRE. From a graphic point of view, these areas are clearly identified with colours tending towards orange/red and are located more or less in the central part of both citrus groves.

Considering that the monitoring was conducted shortly before the start of the fruit harvesting period, the identification of these inhomogeneities, combined with the low values of the indices measured in general, is symptomatic of problems related to the state of health of the orange trees in the two test fields, with evident reductions in their productivity.

To better understand whether the encountered criticalities were due to leaf water stress, nutrient deficiency or the presence of weed pathogens, to the already calculated vegetation indices was also supplemented the study of thermal images and the calculation of the CWSI index. As can be seen from the graphical elaborations in Fig.6 and 7, in fact, although the temperature ranges recorded by the thermal sensor in the Ispica and Pontevecchio fields are comparable (ranging from a minimum of 7.10°C to a maximum of 40°C), the water stress index values calculated using the statistical approach in the two test areas highlight two quite different conditions. In light of a CWSImax of 0.04 in the citrus grove in Pontevecchio, i.e. decidedly low, in the Ispica orchard, crop water stress levels are much higher, with a CWSI index that reaches values above 0.5. The recognition of this critical condition is therefore consistent with what emerged from the study of the other vegetation indices which, for the Ispica citrus grove, had returned very low values: this is probably due to a water stress condition that can be resolved by implementing irrigation techniques On the other hand, the homogeneous spatial distribution of CWSI values both in Ispica and Pontevecchio fields does not seem to justify the different concentrations of photosynthetic activity highlighted by the chlorophyll indices. As they are not caused by localised water stress, the areas characterised by low CI and CVI values could be due to nutrient deficiencies or the presence of weeds and other pathogens. In this respect, future research developments could supplement these analyses with specific investigations of soil composition, to identify nutrient deficiencies more precisely and to be able to rationally plan targeted fertiliser campaigns or whatever else is necessary.

In summary, through the calculation of the different vegetation indices, it was possible to recognise a substantial difference between the good vigour of the orange trees cultivated in the field in the Pontevecchio locality compared to those in the citrus grove near Ispica, while the comparison with the water stress indicators made it possible to understand how this diversity is substantially due to a greater lack of water near Ispica (mean CWSI = 0.5) compared to that measured in the Pontevecchio locality (mean CWSI = 0.04).

By analysing the spatial localisation of the individual values (Figg.6-7), it was also possible to understand how the leaf water content identified by the CWSI index, although higher in Pontevecchio and lower in Ispica, is in fact homogeneously distributed within each field (the colours on the map are

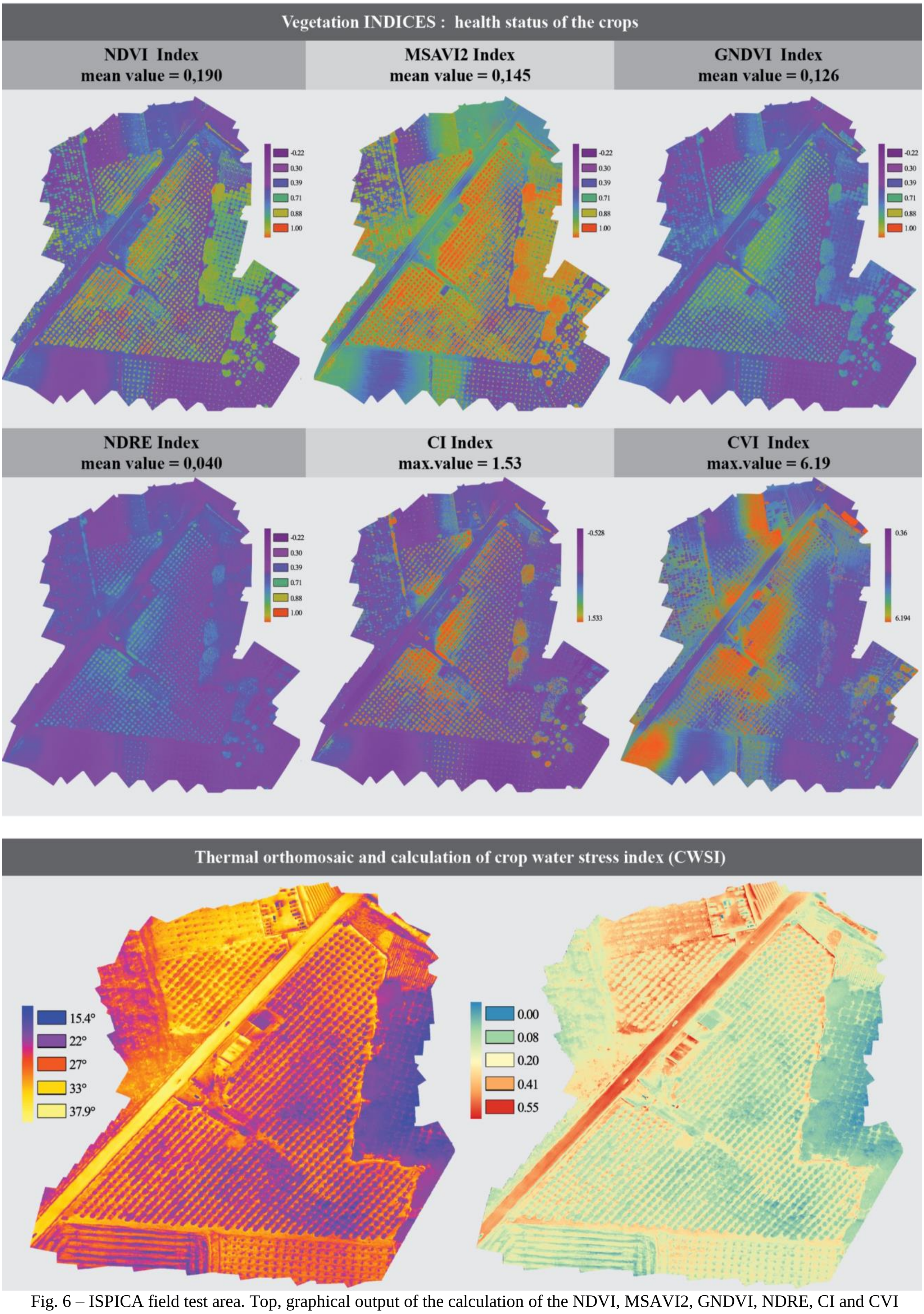

Fig. 6 – ISPICA field test area. Top, graphical output of the calculation of the NDVI, MSAVI2, GNDVI, NDRE, CI and CVI vegetation indices. Bottom, thermal image and graphic output of the crop water stress index: comparative views.

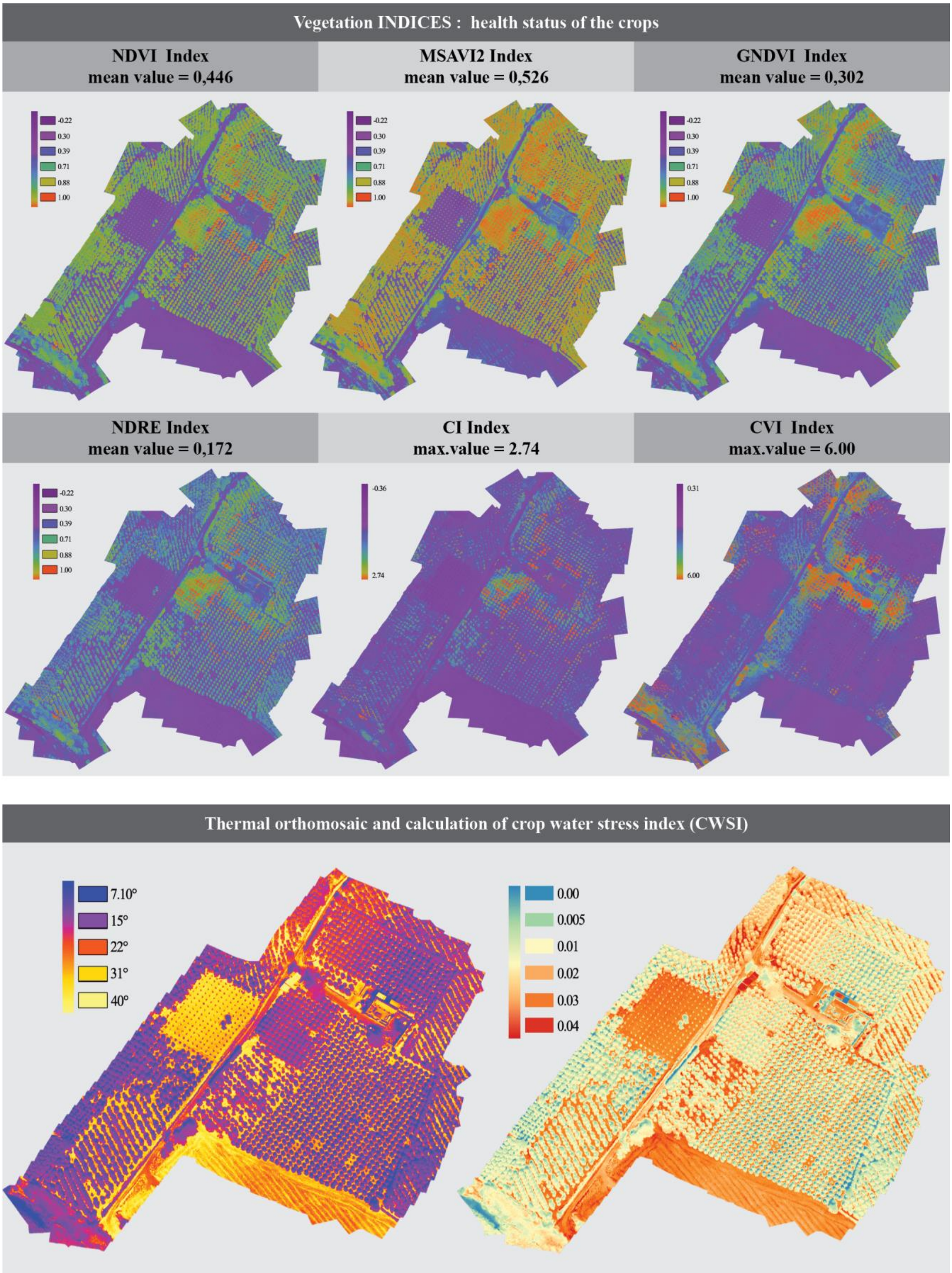

Fig. 7 – PONTEVECCHIO field test area. Top, graphical output of the calculation of the NDVI, MSAVI2, GNDVI, NDRE, CI and CVI vegetation indices. Bottom, thermal image and graphic output of the crop water stress index: comparative views.

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uniform and do not present localised peaks), unlike the uneven concentrations of photosynthetic activity highlighted by the CI and CVI indices (areas tending towards red). This fundamental finding allowed us not only to identify areas where crops are not fully healthy, but also to understand how this reduced vigour is attributable to nutrient deficiency or the presence of bacteria/pathogens, rather than localised water stress.

6. Conclusions

The results of the study presented in this paper highlight how precision agriculture is introducing important innovations in the management of the agricultural sector, making it more efficient and sustainable. In particular, the investigations presented in this work constitute, at a national level, a virtuous and innovative example of best practice that aims not only to localize agronomic criticalities but also to understand their causes by integrating the use of multispectral sensors installed on drones (indirect recognition of the state of vigor of crops starting from the calculation of traditional vegetation indices), with the processing of specific indicators of crop water content through temperature data recorded by UAV-mounted thermal cameras. This is an innovative and effective approach that can certainly be applied in further different contexts of productive green as it provides analytical tools and operational methods to monitor the health of crops in real time, allowing timely and targeted interventions only where necessary, optimising the use of resources and reducing waste. In the future developments, an important contribution will certainly be provided by the integration of these analyses with specific studies related both to other climatic factors (especially in relation to CO2 and nitrogen concentrations in atmosphere) and to the physical-chemical characteristics of the soil, to even better optimise agricultural operations, reducing the risk of soil and water pollution and, also in relation to the state of the atmosphere, the increase in the anthropogenic greenhouse effect.

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